

# Capstone Project - The Battle of Neighborhoods Report

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## 1. Introduction

### 1. Background

The average American moves about eleven times in their lifetime. This brings us to the question: Do people move until they find a place to settle down where they truly feel happy, or do our wants and needs change over time, prompting us to eventually leave a town we once called home for a new area that will bring us satisfaction? Or, do we too often move to a new area without knowing exactly what we're getting into, forcing us to turn tail and run at the first sign of discomfort?

To minimize the chances of this happening, we should always do proper research when planning our next move in life. Consider the following factors when picking a new place to live so you don't end up wasting your valuable time and money making a move you'll end up regretting. Safety is a top concern when moving to a new area. If you don't feel safe in your own home, you're not going to be able to enjoy living there.

### 2. Problem

The crime statistics dataset of London found on Kaggle has crimes in each Boroughs of London from 2008 to 2016. The year 2016 being the latest we will be considering the data of that year which is actually old information as of now. The crime rates in each borough may have changed over time.

This project aims to select the safest borough in London based on the total crimes, explore the neighborhoods of that borough to find the 10 most common venues in each neighborhood and finally cluster the neighborhoods using k-mean clustering.

### 3. Interest

Expats who are considering to relocate to London will be interested to identify the safest borough in London and explore its neighborhoods and common venues around each neighborhood.

## 2. Data Acquisition and Cleaning

### 1. Data Acquisition

The data acquired for this project is a combination of data from three sources. The first data source of the project uses a [London crime data](#) that shows the crime per borough in London. The dataset contains the following columns:

- **Isao\_code**: code for Lower Super Output Area in Greater London.
- **borough**: Common name for London borough.

- **major\_category**: High level categorization of crime
- **minor\_category**: Low level categorization of crime within major category.
- **value**: monthly reported count of categorical crime in given borough

- **year:** Year of reported counts, 2008-2016
- **month:** Month of reported counts, 1-12

The second source of data is scraped from a wikipedia page that contains the [list of London boroughs](#). This page contains additional information about the boroughs, the following are the columns:

- **Borough:** The names of the 33 London boroughs.
- **Inner:** Categorizing the borough as an Inner London borough or an Outer London Borough.
- **Status:** Categorizing the borough as Royal, City or other borough.
- **Local authority:** The local authority assigned to the borough.
- **Political control:** The political party that control the borough.
- **Headquarters:** Headquarters of the Boroughs.
- **Area (sq mi):** Area of the borough in square miles.
- **Population (2013 est)[1]:** The population in the borough recorded during the year 2013.
- **Co-ordinates:** The latitude and longitude of the boroughs.
- **Nr. in map:** The number assigned to each borough to represent visually on a map.

The third data source is the [list of Neighborhoods in the Royal Borough of Kingston upon Thames](#), as found on a wikipedia page. This dataset is created from scratch using the list of neighborhood available on the site, the following are columns:

- **Neighborhood:** Name of the neighborhood in the Borough.
- **Borough:** Name of the Borough.
- **Latitude:** Latitude of the Borough.
- **Longitude:** Longitude of the Borough.

## 2.2 Data Cleaning

The data preparation for each of the three sources of data is done separately. From the London crime data, the crimes during the most recent year (2016) are only selected. The major categories of crime are pivoted to get the total crimes per the boroughs for each major category (see *fig 2.1*).

	Borough	Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	Total
0	Barking and Dagenham	1287	1949	919	378	534	5607	6067	16741
1	Barnet	3402	2183	906	499	464	9731	7495	24684
2	Bexley	1123	1673	646	294	209	4392	4503	12840
3	Brent	2631	2280	2096	538	919	9026	9205	26693
4	Bromley	2214	2202	728	417	389	7584	6650	20164

*Fig 2.1 London crime data after preprocessing*

The second data is scraped from a wikipedia page using the **Beautiful Soup** library in python. Using this library we can extract the data in the tabular format as shown in the website. After the web scraping, string manipulation is required to get the names of the

boroughs in the correct form (see *fig 2.2*). This is important because we will be merging the two datasets together using the Borough names.

	Borough	Inner	Status	Local authority	Political control	Headquarters	Area (sq mi)	Population (2013 est)[1]	Co-ordinates	Nr. in map
0	Barking and Dagenham	NaN	NaN	Barking and Dagenham London Borough Council	Labour	Town Hall, 1 Town Square	13.93	194352	51°33'39"N 0°09'21"E / 51.5607°N 0.1557°E / ...	25
1	Barnet	NaN	NaN	Barnet London Borough Council	Conservative	North London Business Park, Oakleigh Road South	33.49	369088	51°37'31"N 0°09'06"W / 51.6252°N 0.1517°W / ...	31
2	Bexley	NaN	NaN	Bexley London Borough Council	Conservative	Civic Offices, 2 Watling Street	23.38	236687	51°27'18"N 0°09'02"E / 51.4549°N 0.1505°E / ...	23
3	Brent	NaN	NaN	Brent London Borough Council	Labour	Brent Civic Centre, Engineers Way	16.70	317264	51°33'32"N 0°16'54"W / 51.5588°N 0.2817°W / ...	12
4	Bromley	NaN	NaN	Bromley London Borough Council	Conservative	Civic Centre, Stockwell Close	57.97	317899	51°24'14"N 0°01'11"E / 51.4039°N 0.0198°E / ...	20

*Fig 2.2 List of London Boroughs*

The two datasets are merged on the Borough names to form a new dataset that combines the necessary information in one dataset (see *fig 2.3*). The purpose of this dataset is to visualize the crime rates in each borough and identify the borough with the least crimes recorded during the year 2016.

	Borough	Local authority	Political control	Headquarters	Area (sq mi)	Population (2013 est)[1]	Co-ordinates	Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	Total
0	Barking and Dagenham	Barking and Dagenham London Borough Council	Labour	Town Hall, 1 Town Square	13.93	194352	51°33'39"N 0°09'21"E / 51.5607°N 0.1557°E / ...	1287	1949	919	378	534	5607	6067	16741
1	Barnet	Barnet London Borough Council	Conservative	North London Business Park, Oakleigh Road South	33.49	369088	51°37'31"N 0°09'06"W / 51.6252°N 0.1517°W / ...	3402	2183	906	499	464	9731	7499	24684
2	Bexley	Bexley London Borough Council	Conservative	Civic Offices, 2 Watling Street	23.38	236687	51°27'18"N 0°09'02"E / 51.4549°N 0.1505°E / ...	1123	1673	646	294	209	4392	4503	12640
3	Brent	Brent London Borough Council	Labour	Brent Civic Centre, Engineers Way	16.70	317264	51°33'32"N 0°16'54"W / 51.5588°N 0.2817°W / ...	2631	2280	2096	536	919	9026	9205	26693
4	Bromley	Bromley London Borough Council	Conservative	Civic Centre, Stockwell Close	57.97	317899	51°24'14"N 0°01'11"E / 51.4039°N 0.0198°E / ...	2214	2202	726	417	368	7864	6650	20164

*Fig 2.3 London Borough Crime*

After visualizing the crime in each borough we can find the borough with the lowest crime rate and hence tag that borough as the safest borough. The third source of data is acquired from the list of neighborhoods in the safest borough on wikipedia. This dataset is created from scratch, the pandas data frame is created with the names of the neighborhoods and the name of the borough with the latitude and longitude left blank (see *fig 2.4*).

	Neighborhood	Borough	Latitude	Longitude
0	Berrylands	Kingston upon Thames		
1	Canbury	Kingston upon Thames		
2	Chessington	Kingston upon Thames		
3	Coombe	Kingston upon Thames		
4	Hook	Kingston upon Thames		

*Fig 2.4 Neighborhoods of the safest borough*



The coordinates of the neighborhoods is be obtained using **Google Maps API geocoding** to get the final dataset (See *Fig 2.5*).

	Neighborhood	Borough	Latitude	Longitude
0	Berrylands	Kingston upon Thames	51.393781	-0.284802
1	Canbury	Kingston upon Thames	51.417499	-0.305553
2	Chessington	Kingston upon Thames	51.358336	-0.298622
3	Coombe	Kingston upon Thames	51.419450	-0.265398
4	Hook	Kingston upon Thames	51.367898	-0.307145

*Fig 2.5 Neighborhoods of the safest borough*

The new dataset is used to generate the 10 most common venues for each neighborhood using the Foursquare API, finally using k means clustering algorithm to cluster similar neighborhoods together.

### 3. Methodology

#### 1. Exploratory Data Analysis

##### 1. Statistical summary of crimes

The describe function in python is used to get statistics of the London crime data, this returns the mean, standard deviation, minimum, maximum, 1st quartile (25%), 2nd quartile (50%), and the 3rd quartile (75%) for each of the major categories of crime (See *fig 3.1.1*).

	Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	Total
count	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000
mean	2069.242424	1941.545455	1179.212121	479.060606	682.866667	8913.121212	7041.848485	22306.696970
std	737.448644	625.207070	586.406416	223.298698	441.425366	4620.565054	2513.601551	8828.228749
min	2.000000	2.000000	10.000000	6.000000	4.000000	129.000000	25.000000	178.000000
25%	1531.000000	1650.000000	743.000000	378.000000	377.000000	5919.000000	5936.000000	16903.000000
50%	2071.000000	1989.000000	1063.000000	490.000000	599.000000	8925.000000	7409.000000	22730.000000
75%	2631.000000	2351.000000	1617.000000	551.000000	936.000000	10789.000000	8832.000000	27174.000000
max	3402.000000	3219.000000	2738.000000	1305.000000	1822.000000	27520.000000	10834.000000	48330.000000

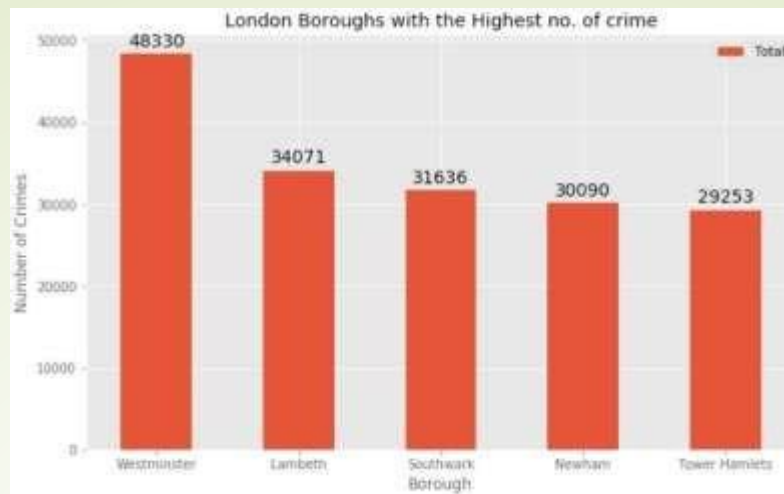
*Fig 3.1.1 Statistical description of the London crimes*

The count for each of the major categories of crime returns the value 33 which is the number of London boroughs. 'Theft and Handling' is the highest reported crime during the year 2016 followed by 'Violence against the person', 'Criminal damage'. The lowest recorded crimes are 'Drugs', 'Robbery' and 'Other Notifiable offenses'.

##### 3.1.2 Boroughs with the highest crime rates

Comparing five boroughs with the highest crime rate during the year 2016 it is evident that Westminster has the highest crimes recorded followed by Lambeth, Southwark, Newham

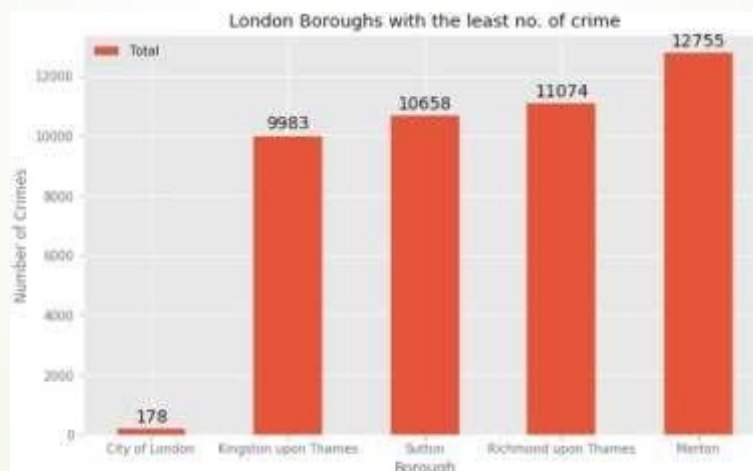
and Tower Hamlets. Westminster has a significantly higher crime rate than the other 4 boroughs (see *fig 3.1.2*).



*Fig 3.1.2 Boroughs with the highest crime rates*

### 3.1.3 Boroughs with the lowest crime rates

Comparing five boroughs with the lowest crime rate during the year 2016, City of London has the lowest recorded crimes followed by Kingston upon Thames, Sutton, Richmond upon Thames and Merton (see *fig 3.1.3*).



*Fig 3.1.3 Boroughs with the lowest crime rates*

City of London has a significantly lower crime rate because it is the 33rd principal division of Greater London but it is not a London borough. It has an area of 1.12 square miles and a population of 7000 as of 2013 which suggests that it is a small area (see *fig 3.1.3.1*). Hence we will consider the next borough with the lowest crime rate as the safest borough in London which is Kingston upon Thames.

	Borough	Total	Area (sq mi)	Population (2013 est)[1]
6	City of London	178	1.12	7000

*Fig 3.1.3.1 City of London*

### 3.1.4 Neighborhoods in Kingston upon Thames

There are 15 neighborhoods in the royal borough of Kingston upon Thames, they are visualized on a map using folium on python (see *fig 3.1.4*).



*Fig 3.1.4 Neighborhoods in Kingston upon Thames*

### 3.2 Modelling

Using the final dataset containing the neighborhoods in Kingston upon Thames along with the latitude and longitude, we can find all the venues within a 500 meter radius of each neighborhood by connecting to the Foursquare API. This returns a json file containing all the venues in each neighborhood which is converted to a pandas dataframe. This data frame contains all the venues along with their coordinates and category (see *fig 3.2.1*).

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Berrylands	51.393781	-0.284802	Surbiton Racket & Fitness Club	51.392676	-0.290224	Gym / Fitness Center
1	Berrylands	51.393781	-0.284802	Alexandra Park	51.394230	-0.281206	Park
2	Berrylands	51.393781	-0.284802	K2 Bus Stop	51.392302	-0.281534	Bus Stop
3	Berrylands	51.393781	-0.284802	Cafe Rosa	51.390175	-0.282490	Café
4	Canbury	51.417499	-0.305553	The Boater's Inn	51.418546	-0.305915	Pub

*Fig 3.2.1 Venue details of each Neighborhood*

One hot encoding is done on the venues data. (One hot encoding is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction). The Venues data is then grouped by the Neighborhood and the mean of the venues are calculated, finally the 10 common venues are calculated for each of the neighborhoods.

To help people find similar neighborhoods in the safest borough we will be clustering similar neighborhoods using K - means clustering which is a form of unsupervised machine learning algorithm that clusters data based on predefined cluster size. We will use a cluster size of 5 for this project that will cluster the 15 neighborhoods into 5 clusters. The reason to



conduct a K- means clustering is to cluster neighborhoods with similar venues together so that people can shortlist the area of their interests based on the venues/amenities around each neighborhood.

#### 4. Results

After running the K-means clustering we can access each cluster created to see which neighborhoods were assigned to each of the cluster. Looking into the neighborhoods in the first cluster (see fig 4.1)

Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	
0	Berrylands	Kingston upon Thames	51.393781	-0.294802	0	Gym / Fitness Center	Park	Bus Stop	Deli / Bodega	Dessert Shop	Discount Store	Donut Shop	Electronics Store	English Restaurant

Fig 4.1 Cluster 1

Looking into the neighborhoods in the second clusters, we can see this cluster have three neighborhoods. (see fig 4.2)

	Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Common Venue
6	Kingston Vale	Kingston upon Thames	51.431850	-0.258138	1	Soccer Field	Grocery Store	Bar	Sandwich Place	Fast Food Restaurant	Department Store	Dessert Shop	Discount Store	
8	Motspur Park	Kingston upon Thames	51.390985	-0.248898	1	Construction & Landscaping	Soccer Field	Park	Gym	Auto Garage	Department Store	Discount Store	Donut Shop	Rest
14	Tolworth	Kingston upon Thames	51.379876	-0.282660	1	Grocery Store	Pharmacy	Hotel	Bus Stop	Sandwich Place	Italian Restaurant	Bowling Alley	Soccer Field	Dis

Fig 4.2 Cluster2

The third cluster has one neighborhood which consists of Venues such as Pub, Train station, and Women's Store shops. (see fig 4.3)

	Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue
11	Old Malden	Kingston upon Thames	51.382484	-0.25909	2	Pub	Train Station	Food	Women's Store	Farmers Market	Deli / Bodega	Department Store	Dessert Shop	Discount Store

Fig 4.3 Cluster 3

The fourth cluster has seven neighborhoods in it, these neighborhoods have common venues such as Gym, Department store Pub, Bus Stops, Restaurants, Electronics Stores and Soccer fields etc.

(see fig 4.4)



	Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue
1	Canbury	Kingston upon Thames	51.417499	-0.305553	3	Pub	Gym / Fitness Center	Spa	Hotel	Indian Restaurant	Fish & Chips Shop	Park	Café
4	Hook	Kingston upon Thames	51.367898	-0.307145	3	Fish & Chips Shop	Bakery	Indian Restaurant	Supermarket	Women's Store	Department Store	Dessert Shop	Discount Store
5	Kingston upon Thames	Kingston upon Thames	51.409627	-0.306262	3	Coffee Shop	Café	Pub	Clothing Store	Italian Restaurant	Department Store	Bakery	Thai Restaurant
9	New Malden	Kingston upon Thames	51.405335	-0.263407	3	Korean Restaurant	Gym	Gastropub	Bar	Sushi Restaurant	Supermarket	Indian Restaurant	Women's Store
10	Norbiton	Kingston upon Thames	51.409999	-0.287396	3	Indian Restaurant	Italian Restaurant	Pub	Food	Pizza Place	Breakfast Spot	Coffee Shop	Pharmacy
12	Seething Wells	Kingston upon Thames	51.392642	-0.314368	3	Indian Restaurant	Coffee Shop	Pub	Gym / Fitness Center	Café	Gourmet Shop	Gym	Harbor / Marina
13	Surbiton	Kingston upon Thames	51.393756	-0.303310	3	Coffee Shop	Pub	Platform	Grocery Store	Italian Restaurant	Pharmacy	Breakfast Spot	Gourmet Shop

Fig 4.4 Cluster 5

The fifth cluster has one neighborhood which consists of Venues such as Grocery shops, Pub, Restaurants, and Department stores. (see fig 4.5). We will look into the neighborhoods in the fourth cluster (see fig 4.4).

	Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue
7	Malden Rushett	Kingston upon Thames	51.341052	-0.319076	4	Grocery Store	Pub	Garden Center	Restaurant	Farmers Market	Deli / Bodega	Department Store	Dessert Shop	Discount Store

Fig 4.5 Cluster 4

The fourth cluster has two neighborhoods in it, these neighborhoods have common venues such as Parks, Gym/Fitness centers, Bus Stops, Restaurants, Electronics Stores and Soccer fields etc.

Visualizing the clustered neighborhoods on a map using the folium library (see fig 4.6).

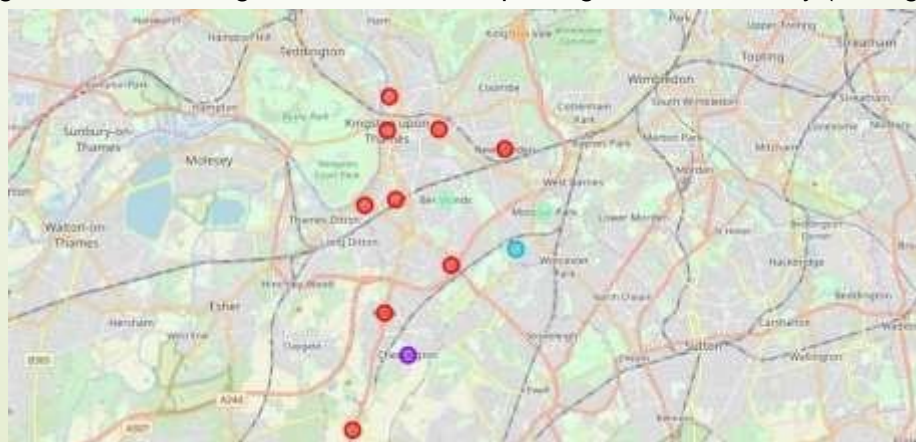


Fig 4.6 Clustered neighborhoods in the Borough of Kingston upon Thames

Each cluster is color coded for the ease of presentation, we can see that majority of the neighborhood falls in the red cluster which is the first cluster. Three neighborhoods have their own cluster (Blue, Purple and Yellow), these are clusters two three and five. The green cluster consists of two neighborhoods which is the 4th cluster.

## **5. Discussion**

- The aim of this project is to help people who want to relocate to the safest borough in London, expats can chose the neighborhoods to which they want to relocate based on the most common venues in it.
- For example if a person is looking for a neighborhood with good connectivity and public transportation we can see that Clusters 2 and 4 have restaurants, bus stop and Pub stops as the most common venues.
- If a person is looking for a neighborhood with Bus stop, Park and gym in a close proximity, then the neighborhoods in the first cluster is suitable.
- For a family I feel that the neighborhoods in Cluster 4 are more suitable dues to the common venues in that cluster, these neighborhoods have common venues such as Gym, Department store Pub, Bus Stops, Restaurants, Electronics Stores and Soccer fields which is ideal for a family. The choices of neighborhoods may vary from person to person.

## **6. Conclusion**

This project helps a person get a better understanding of the neighborhoods with respect to the most common venues in that neighborhood. It is always helpful to make use of technology to stay one step ahead i.e. finding out more about places before moving into a neighborhood. We have just taken safety as a primary concern to shortlist the safest borough of London. The future of this project includes taking other factors such as cost of living in the areas into consideration to shortlist the borough, such as filtering areas based on a predefined budget.